# Sensitivity of crop model predictions to entire meteorological and soil input datasets highlights vulnerability to drought

Mark Pogson*, Astley Hastings, Pete Smith

School of Biological Sciences, University of Aberdeen, 23 St Machar Drive, Aberdeen AB24 3UU, UK
*corresponding author, email: m.pogson@bolton.ac.uk

Please cite as:

**M Pogson, A Hastings, P Smith (2012). Sensitivity of crop model predictions to entire meteorological and soil input datasets highlights vulnerability to drought. Environmental Modelling & Software 29: 37-43, doi: 10.1016/j.envsoft.2011.10.008**

## Abstract

Crop growth models are increasingly used as part of research into areas such as climate change and bioenergy, so it is particularly important to understand the effects of environmental inputs on model results. Rather than investigating the effects of separate input parameters, we assess results obtained from a crop growth model using a selection of entire meteorological and soil input datasets, since these define modelled conditions. Yields are found to vary significantly only where the combination of inputs makes the crop vulnerable to drought, rather than being especially sensitive to any single input. Results highlight the significance of soil water parameters, which are likely to become increasingly critical in areas affected by climate change. Differences between datasets demonstrate the need to consider the dataset-dependence of parameterised model terms, both for model validation and predictions based on alternative datasets.

Keywords: crop growth model; input data; sensitivity analysis; soil water; drought; parameterisation

## 1. Introduction

Crop growth models have been used in agricultural research for several decades to help understand and predict the behaviour of crops under different conditions (Bouman et al., 1996). Recent interest in areas such as the effects of climate change on food supply (Lobell et al., 2008), potential carbon mitigation by agriculture (Smith et al., 2000) and the use of biomass as an energy source (Bringezu et al., 2009) has increased the importance of accurate crop growth modelling.

Most crop growth models depend on careful fitting of parameters with experimental data (Guo et al., 2006). The effect that an individual input parameter, such as air temperature, has on model behaviour is generally well studied as part of the modelling process (Smith and Smith, 2007), and previous work has investigated the relative significance of their effects (Aggarwal, 1995; Ruget et al., 2002; Varella et al., 2010). However, the overall role of environmental inputs, including entire spatial datasets of drivers, has not been thoroughly explored, yet model conditions are generally defined by these datasets and thus their effects should be considered in combination and not just individually.

Understanding sensitivity and uncertainty is central to environmental modelling (Nossent et al., 2011; Refsgaard et al., 2007; Smith and Smith, 2007; Warmink et al., 2010), and the use of meteorological and soil data is common to a range of subject areas (Moussiopolous et al., 2004; Post et al., 2006; Sharples et al., 2009). The effect of different meteorological and soil inputs on model results is therefore of significant interest beyond crop modelling. The use of datasets based on different forms of interpolation (Hijmans et al., 2005) or climate predictions (Southworth et al., 2000) makes it particularly important to understand the sensitivity of model outputs to the choice of data inputs due to the potential range of input values for ostensibly the same conditions.

This study explores the effects of different meteorological and soil datasets on the crop growth model Miscanfor (Hastings et al., 2009) over a fixed time period and land area. The use of different datasets for the same reported environmental conditions should provide a guide to the possible range of model predictions for a given time and area range. In addition to investigating the influence of different datasets on results, the study also provides an indication of the potential sensitivity of crops to environmental changes by analysing differences in model predictions resulting from changing input data. Due to the nature of these results, the role of drought in model predictions is considered in particular detail.

## 2. Methods

### 2.1 The *Miscanfor* model

Miscanfor follows the energy use efficiency approach of Monteith (Monteith, 1977; Clifton-Brown et al., 2000), which is a common method in crop growth modelling (Williams et al., 1989; Ewert, 2004). The model is calibrated for *Miscanthus giganteus,* a $C_4$ rhizomatous perennial grass which is of interest as a bioenergy crop due to its relatively high yields under a range of conditions (Ercoli et al., 1999).

Yield mass is calculated according to meteorological and soil data (Hastings et al., 2009). Meteorological inputs to the model are mean temperature, temperature range, precipitation and cloud cover; soil inputs are field capacity and wilt point. Radiation is calculated from the latitude and time of year by the method described in the SWAT Theoretical Documentation (Neitsch et al., 2002), including a cloud correction factor (Hastings et al., 2009). Potential evapotranspiration is calculated using the Thornthwaite equation (Thornthwaite, 1948), with a Penman adjustment factor (Hastings et al., 2009). Downregulation terms for evapotranspiration, radiation use efficiency and leaf area index are calculated according to available soil water using an Aslyng discontinuous linear process description (Aslyng, 1965; Hastings et al., 2009). The modelled crop is also subject to drought and frost kill (Hastings et al., 2009). Roots are assumed uniformly distributed in the whole soil profile. Growth is calculated according to the product of intercepted photosynthetically active radiation and the empirical radiation use efficiency, which is adjusted for water stress. The Miscanfor model was originally parameterised in Europe using IGBP soil data and CRU TS 2.2 meteorological data. Previous work has shown good agreement of the model with field data (Hastings et al., 2009).

### 2.2 Spatial datasets

The UK is used as the basis for investigations due to its varied climate, its range of potential *Miscanthus* yields, and the existence of multiple sources of meteorological and soil data. The year range 1961-1990 is used due to the availability of multiple data sources and its importance as a base year range for many climate predictions.

Based on these criteria, the following three different meteorological datasets are used in the investigation:

– CRU TS 3.0 provides a time series of monthly data 1901-2006 on a 0.5° grid (Mitchell and Jones, 2005).
– CRU CL 1.0 provides average monthly data 1961-1990 on a 0.5° grid (New et al. 1999).
– UKCP09 25km provides average monthly data 1961-1990 on a 25km grid (Perry and Hollis, 2005).

Two different soil datasets are used in the investigation:
– HWSD provides time-invariant data on a 30 arc-second grid (FAO, 2009).
– IGBP provides time-invariant data on a 5 arc-minute grid (Global Soil Data Task Group, 2000).

Notable differences between soil datasets are likely due the inherent difficulty of providing a single value for grid cells which includes a range of different soil types; the large difference in grid size of the two datasets is likely to make such discrepancies particularly apparent.

2.3 Modelling procedure and analysis

The study is comprised of the following stages:
- The model is run using each combination of meteorological and soil dataset
- Results for mean yield are compared for each combination
- Differences in input values between datasets are compared

The mean annual *Miscanthus* yield is calculated in the UK for the years 1961-1990 using each of the six combinations of meteorological and soil datasets. The CRU TS 3.0 dataset provides data for each year, hence the yield for each individual year can be calculated explicitly, from which the mean is obtained. However, the CRU CL 1.0 and UKCP09 datasets provide only mean data, and the input data must therefore be used to calculate directly the average yield. Available soil water is initialised with the CRU TS 3.0 dataset by running the model for the year 1960 prior to obtaining yields; soil water is initialised with the other two meteorological datasets by running the model once with the same input data prior to obtaining yields.

Previous work has demonstrated the benefits of obtaining average yields from annual calculations rather than using average meteorological data, which inherently smooth out weather conditions (Hastings et al., 2009). It is therefore expected that the CRU TS 3.0 dataset should provide the most accurate meteorological inputs for the model, as individual years are explicitly modelled. However, since all datasets are intended to represent the same time period and area, the investigation should provide a good indication of the possible range of results obtained for ostensibly the same conditions.

The model calculates results for each soil grid point; the corresponding meteorological grid point is always larger and overlaps its centre. To compare results obtained from different datasets, all are put on the highest resolution grid, and locations ignored where data do not exist for one or more input. Because HWSD does not directly provide data for wilt point and field capacity, values are derived from the bulk density and texture of the soil layers using the Campbell method (Campbell, 1985). The role of pedotransfer functions is considered further in Section 4.1.

Comparisons are performed between model outputs, as well as between environmental inputs. For simplicity, only meteorological inputs for July are presented, since this is arguably the most important month for both crop growth and potential drought. The years 1961, 1975 and 1990 are used to compare the time series dataset with the average datasets, thus giving a spread of years across the time range of interest. Two main statistical measures are used to analyse the data: the correlation coefficient assesses overall similarity of the data, and the coefficient of variation (defined as the standard deviation divided by the magnitude of the mean) measures fluctuations between data for each grid point. A basic sensitivity analysis of yields is also performed to help understand results, using a one-factor-at-a-time method. Although this is not comprehensive (Saltelli and Annoni, 2010), it is straightforward to interpret and is sufficient for the purposes of the investigation.

# 3. Results

## 3.1 Yields

Correlation coefficients between dry matter yields obtained from different combinations of input datasets are shown in Table 1. Correlation is generally stronger between results obtained using the same soil dataset (top left and bottom right corners of table) and weaker for results from different soil datasets (bottom left corner of table).

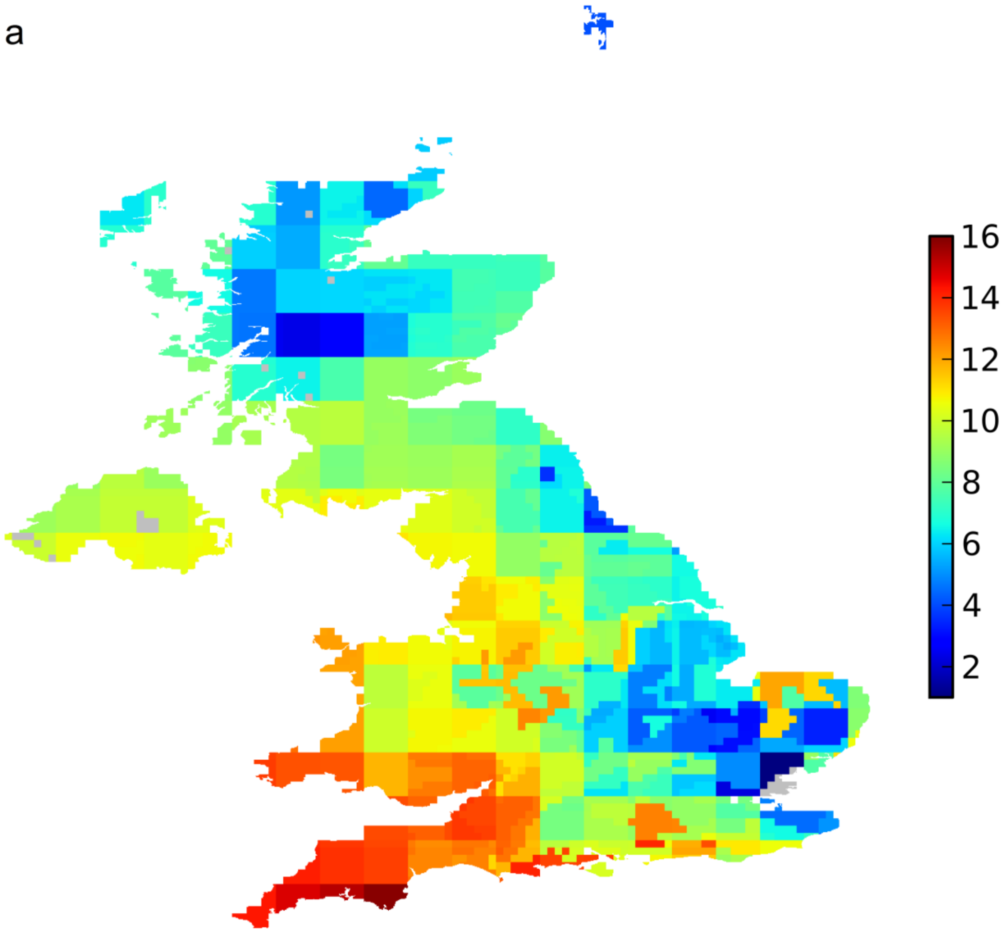
Table 1. Correlation coefficients between model results for dry matter yield using different combinations of input datasets. Soil data (I=IGBP, H=HWSD), meteorological data (T=CRU TS 3.0, A=CRU CL 1.0, U=UKCP09).

| | *I,T* | *I,A* | *I,U* | *H,T* | *H,A* | *H,U* |
|---|---|---|---|---|---|---|
| *I,T* | 1 | | | | | |
| *I,A* | 0.96 | 1 | | | | |
| *I,U* | 0.9 | 0.93 | 1 | | | |
| *H,T* | 0.75 | 0.62 | 0.6 | 1 | | |
| *H,A* | 0.86 | 0.79 | 0.73 | 0.9 | 1 | |
| *H,U* | 0.74 | 0.68 | 0.71 | 0.78 | 0.81 | 1 |

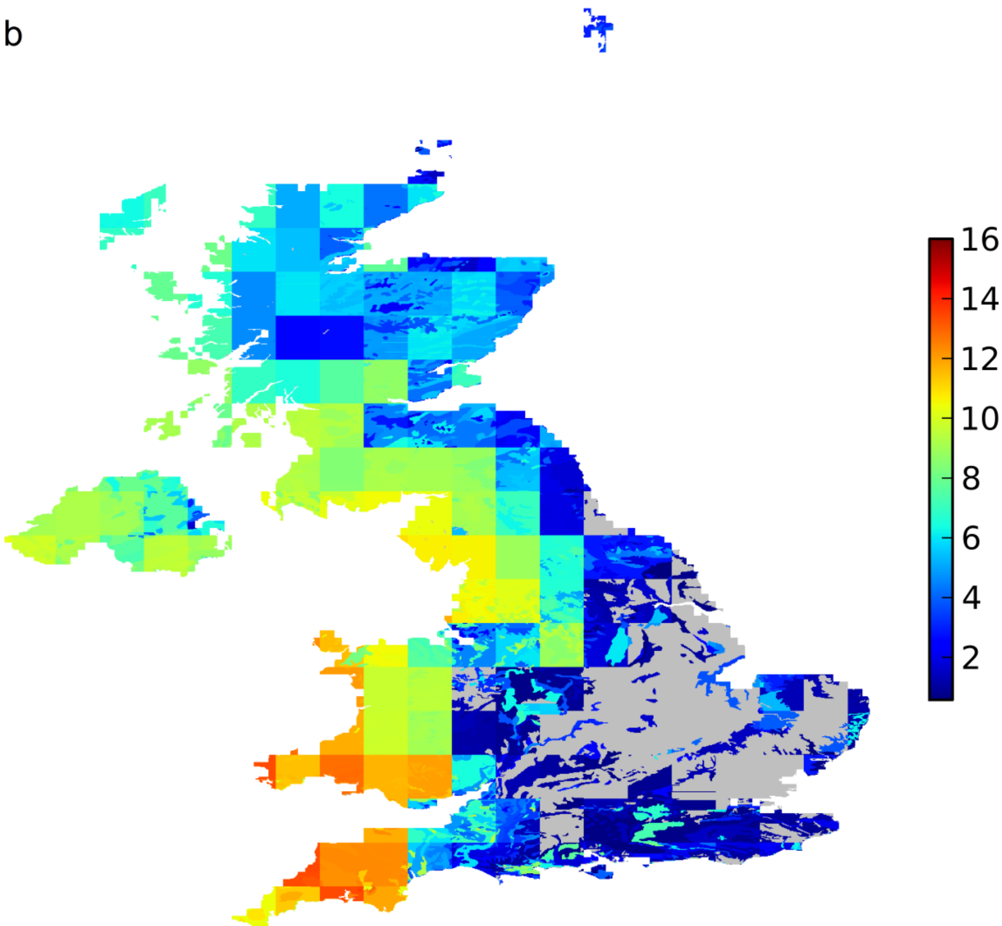
As an example, the yields obtained from the CRU TS 3.0 dataset with both soil datasets are shown in Fig. 1. A large difference in yield is evident in the south-east of the country between the different soil inputs, with high levels of drought kill apparent using HWSD. Similar soil differences are found with other meteorological inputs (results not shown for simplicity).

Fig. 1. Mean annual yield (t/ha) for different input datasets: I,T (a) and H,T (b). Grey areas show no growth (crop kill).

a




b



The coefficient of variation between results is shown for each grid point in Fig. 2a. Greatest variation is in the south-east, which tends to be the driest and warmest area of the UK rather than prone to more variable weather. Fig. 2b shows which combination of input datasets produces the highest yield for each grid point. Results from the IGBP soil dataset tend to produce the highest yield; locations where the HWSD soil data produce the highest yield are quite sparse, and are limited to the west and north of the UK, which tend to be wetter and cooler respectively. Differences between the best and worst dry matter yields are shown in Fig. 2c, demonstrating the significance of the choice of dataset inputs on results.

Fig. 2. (a) Coefficient of variation between results obtained from different combinations of input datasets. Cross shows location used in Fig. 3. (b) Combination of input data which produces the highest yield. (c) Difference between best and worst dry matter yield due to different input datasets (t/ha).

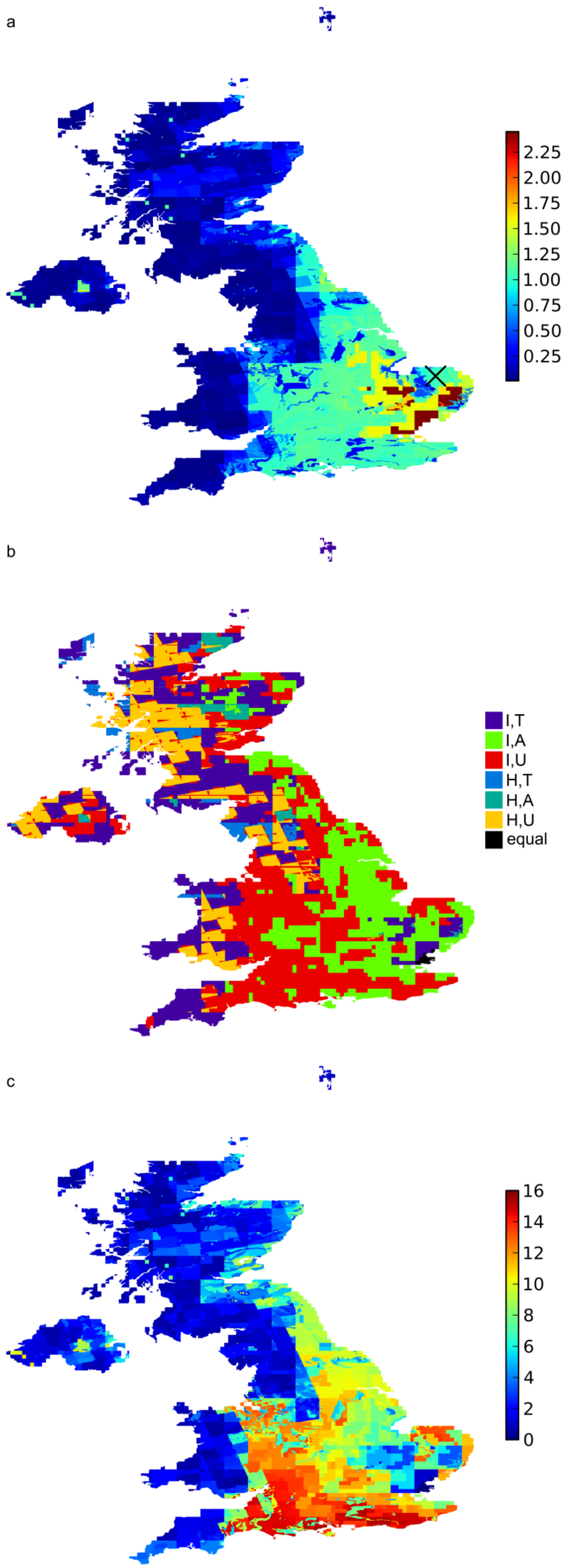
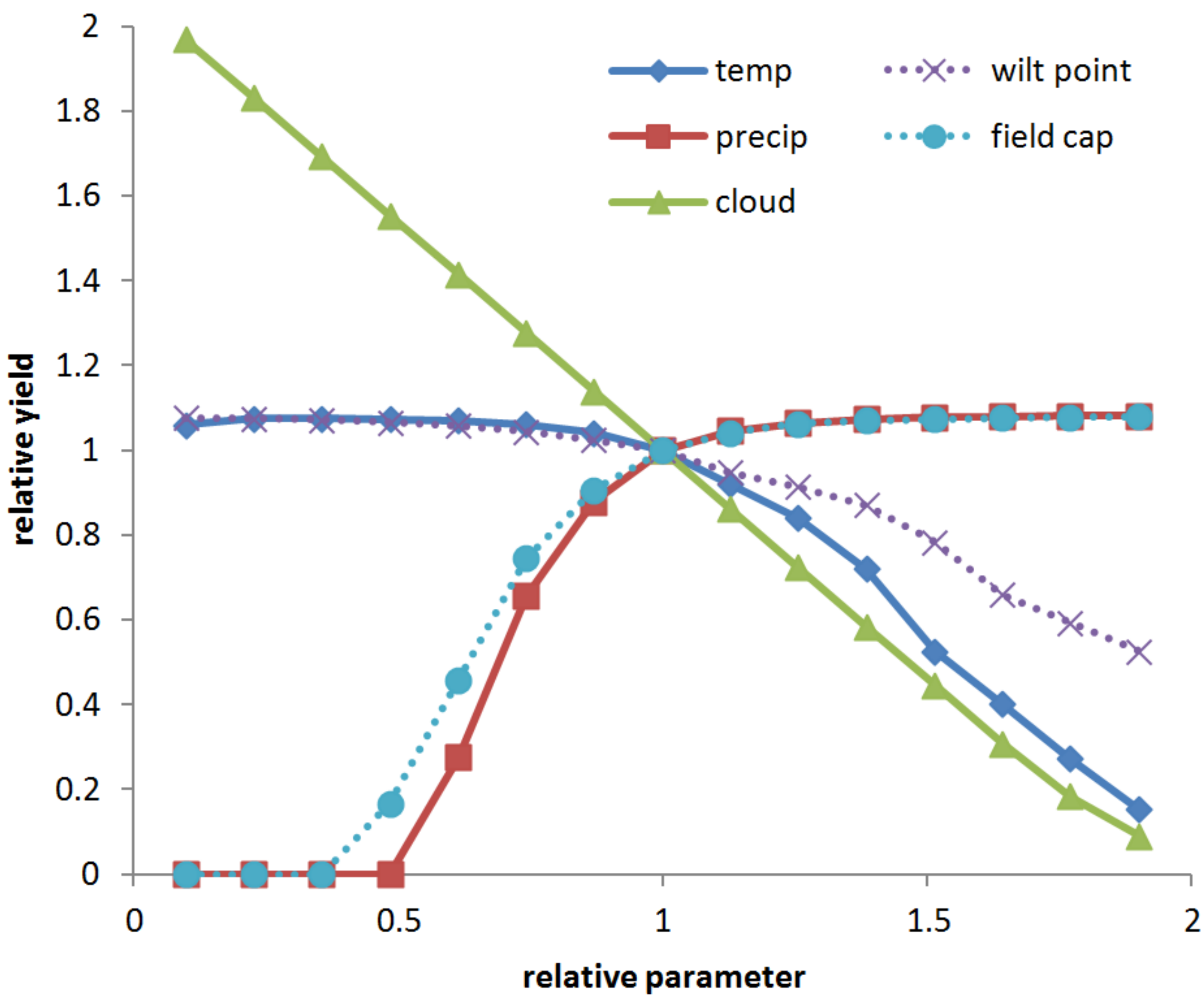

a
2.25
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
b
I,T
I,A
I,U
H,T
H,A
H,U
equal
c
16
14
12
10
8
6
4
2
0

Fig. 3 shows the effect on yields due to varying individual input parameters for a single location in East Anglia (shown by a cross in Fig. 2a), 1961-1990, with results obtained using the combination of IGBP and CRU TS 3.0 datasets. In the region considered, temperature range does not affect results, and is not plotted. With all other parameters held constant, increasing temperature has an increasingly negative effect on yield in the range considered, due to the reduction of available water resulting from increased evapotranspiration. The only exception to this is at the very bottom of the temperature range considered, where drought effects appear marginally outweighed by increased degree days. Increasing cloud cover has a consistently negative effect on growth due to decreased incident radiation. In contrast, increasing precipitation has a positive effect on growth, which levels off for low and high values, where drought and saturation occur respectively. Increasing field capacity has a very similar effect on growth to precipitation, as it increases available water in a comparable manner. Similarly, increasing wilt point follows a pattern resembling that of increasing temperature, since it also reduces available water.

Fig. 3. Sensitivity analysis showing resultant yield from varying individual input parameters. Dotted lines are soil parameters. Location shown by cross in Fig. 2a. Results obtained using IGBP soil data and CRU TS 3.0 meteorological data.




Comparison of yields in Table 1 suggests that variation in soil inputs causes greater changes in results than variation in meteorological inputs. However, Fig. 3 suggests that the model is no more sensitive to soil values in the parameter space considered, hence the differences apparent in Table 1 must be due to either greater differences between soil data than between meteorological data, or a combination of factors that are not apparent in the sensitivity analysis, which only considers one parameter at a time. An analysis of inputs is therefore performed to further understand the effect on results.

## 3.2 Meteorological inputs

Meteorological inputs are considered first. For simplicity, analysis of temperature range is omitted due to its small effect on results. Correlation coefficients between datasets for the month of July are shown in Table 2. Correlation is generally high, with the lowest correlation being for precipitation between different years of the time series data. This suggests good agreement between datasets.

Coefficients of variation for precipitation are shown in Fig. 4a; only precipitation results are presented since they show greatest variation between datasets, and are also crucial to soil water levels. Differences are generally fairly small, and are in large part due to annual variation in the weather for the time series data. As an example of the expected distribution of precipitation in the UK, the mean precipitation for July from dataset A is shown Fig. 4b. An east-west divide in values is evident, showing some similarities to the distribution of differences in results shown in Fig. 2a. This suggests that results are most vulnerable to fluctuation where there is less precipitation.

Table 2. Correlation coefficients for precipitation (a), temperature (b) and cloud (c) for the July of different datasets (T61,75,09=CRU TS 3.0 1961,75,90; A=CRU CL 1.0; U=UKCP09)

(a)

| | *T61* | *T75* | *T90* | *A* | *U* |
|---|---|---|---|---|---|
| *T61* | 1 | | | | |
| *T75* | 0.84 | 1 | | | |
| *T90* | 0.86 | 0.75 | 1 | | |
| *A* | 0.91 | 0.91 | 0.9 | 1 | |
| *U* | 0.83 | 0.8 | 0.85 | 0.89 | 1 |

(b)

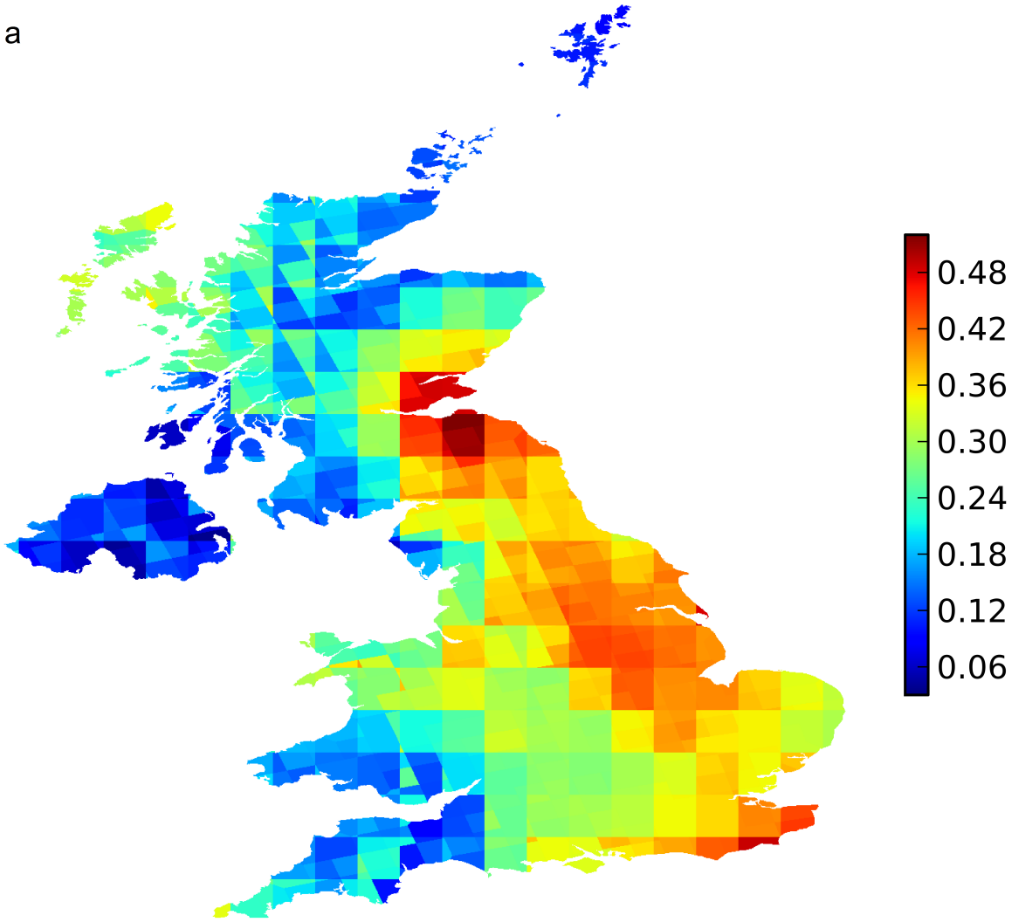
| | *T61* | *T75* | *T90* | *A* | *U* |
|---|---|---|---|---|---|
| *T61* | 1 | | | | |
| *T75* | 0.97 | 1 | | | |
| *T90* | 0.98 | 0.98 | 1 | | |
| *A* | 0.99 | 0.99 | 0.99 | 1 | |
| *U* | 0.93 | 0.94 | 0.94 | 0.95 | 1 |

(c)

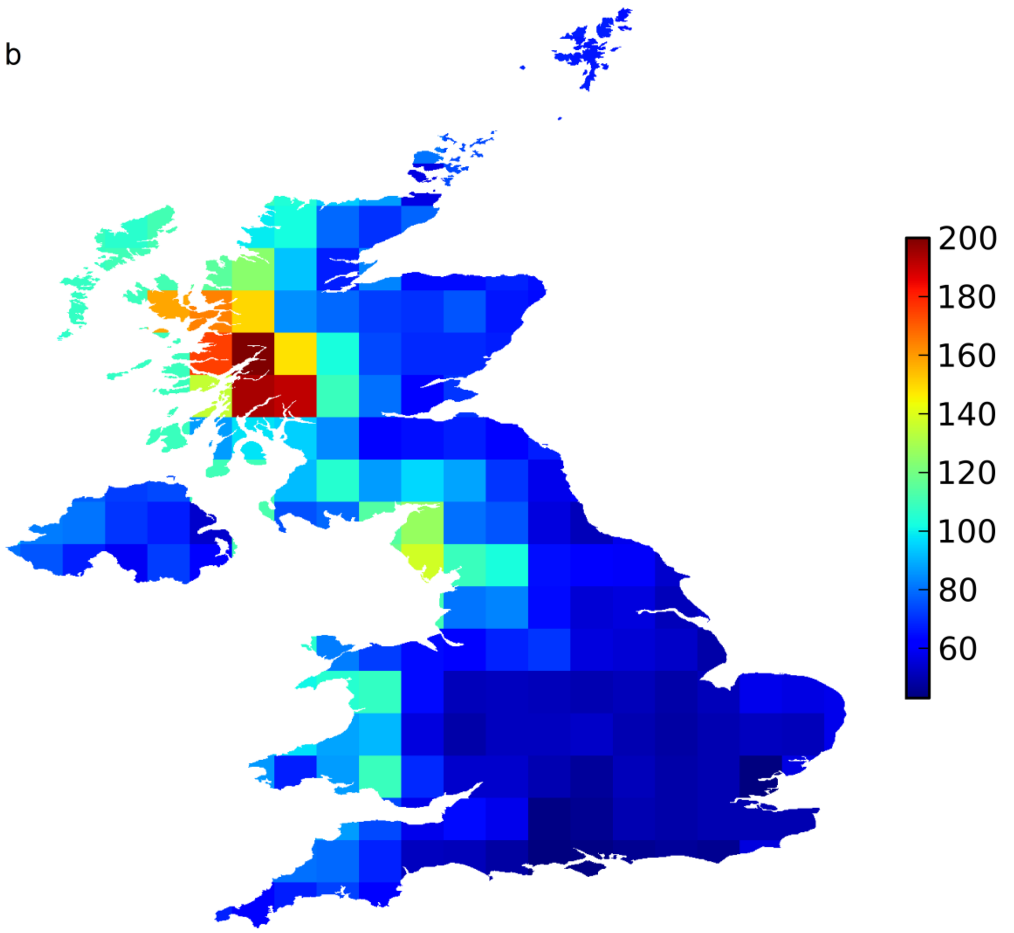
| | *T61* | *T75* | *T90* | *A* | *U* |
|---|---|---|---|---|---|
| *T61* | 1 | | | | |
| *T75* | 0.92 | 1 | | | |
| *T90* | 0.96 | 0.94 | 1 | | |
| *A* | 0.98 | 0.96 | 0.97 | 1 | |
| *U* | 0.9 | 0.88 | 0.93 | 0.9 | 1 |

Fig. 4. (a) Coefficient of variation between input datasets for precipitation in July. (b) Mean July precipitation 1961-1990 (mm) from dataset A (CRU CL 1.0).

a




b

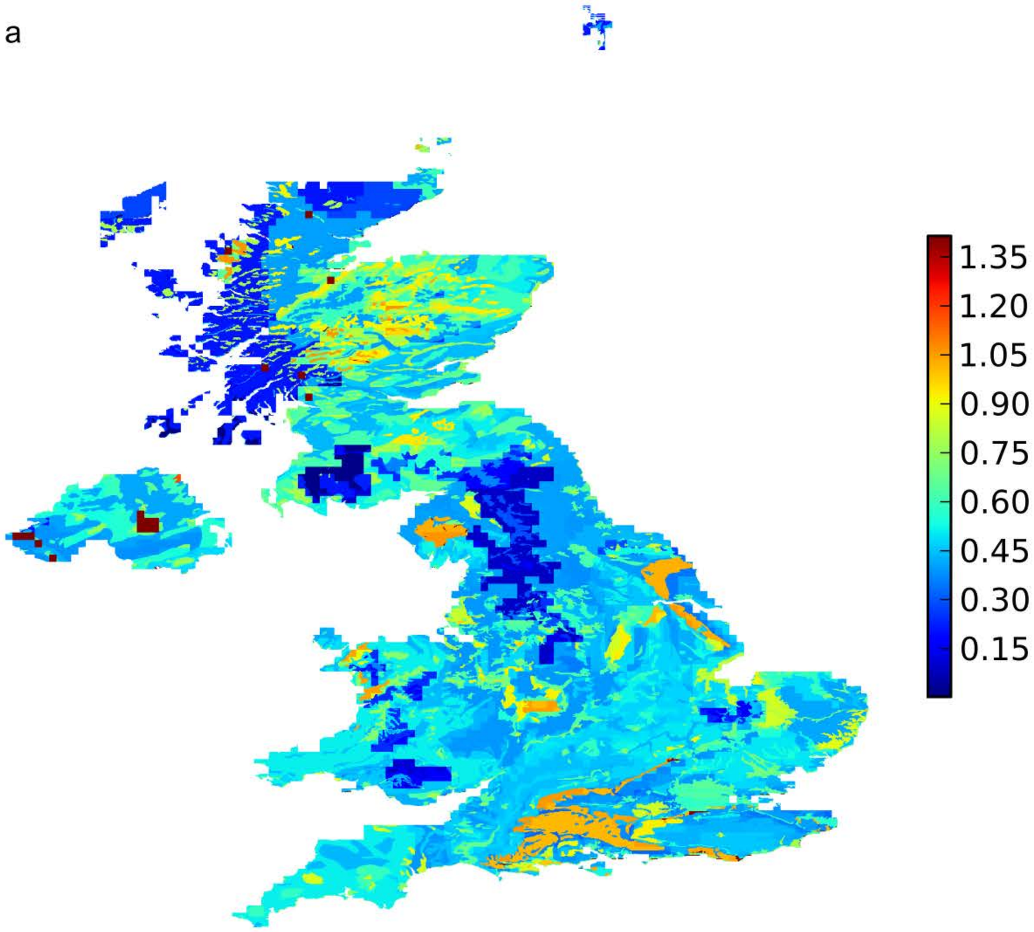


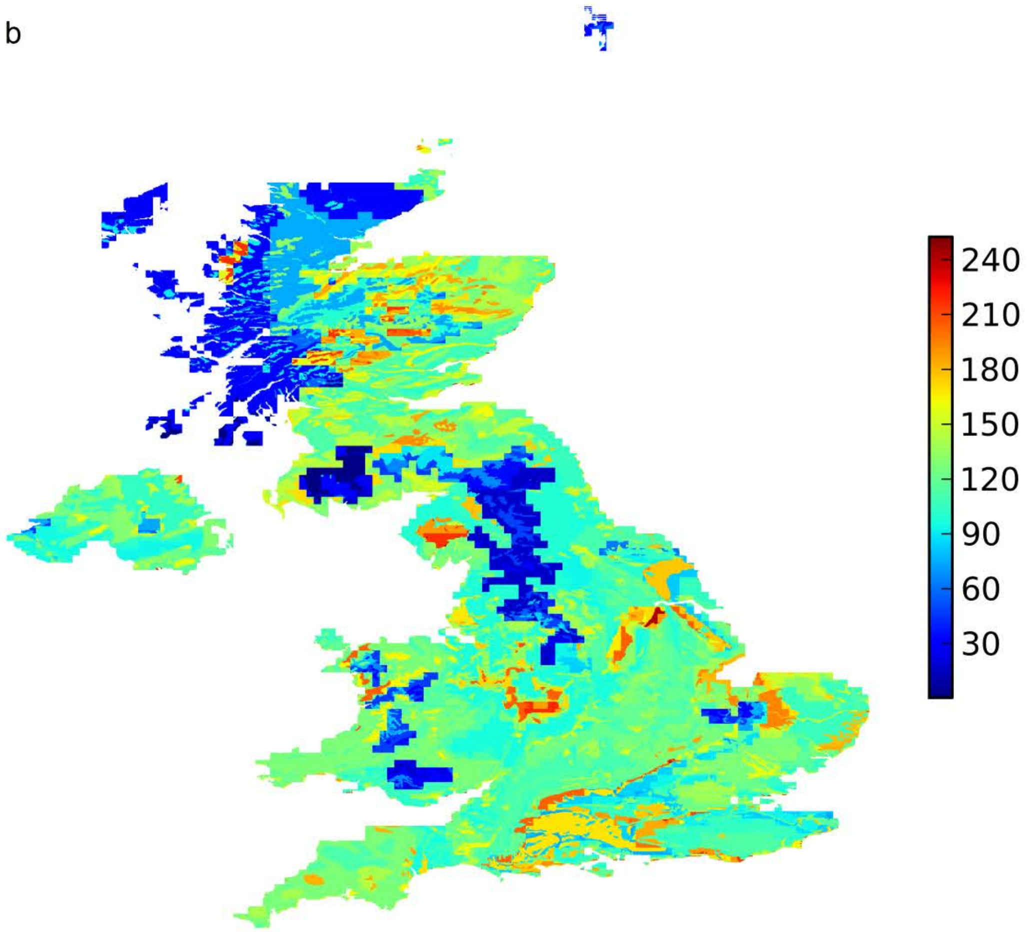
## 3.3 Soil inputs

The correlation coefficient between soil datasets is found to be 0.25 for wilt point and 0.2 for field capacity; the correlation coefficient for the difference between wilt point and field capacity is also 0.2. Correlation is rather weak, and is far lower than for both meteorological data and yield results. Discrepancies are partly explained by the use of derived values from the HWSD dataset, which is considered further in Section 4.1.

In order to simplify analysis, further results are only presented for the difference between field capacity and wilt point, since this is the most important value for crop growth, with higher values likely to favour higher yields. Coefficients of variation are presented in Fig. 5a, showing regions of large differences spread across the whole of the UK. Fig. 5b shows the difference in values between datasets. It should be noted that IGBP has uniformly larger values than HWSD for the whole of the UK, with only a very few exceptions in the northern locations. Differences are often very large, and are fairly randomly distributed. The fact that Fig. 2b shows several location where results obtained using HWSD are larger is because Miscanfor does not depend only on the difference between field capacity and wilt point, but also their individual values, which follow different distributions (results not shown for simplicity).

Fig. 5. (a) Coefficient of variation between IGBP and HWSD soil data for the difference between field capacity and wilt point. (b) Differences between datasets for the difference between field capacity and wilt point (mm). Note that IGBP has consistently larger values than HWSD in all but a very few northern locations.


a
1.35
1.20
1.05
0.90
0.75
0.60
0.45
0.30
0.15


b
240
210
180
150
120
90
60
30

## 4. Discussion

### 4.1 Variation of inputs and outputs

Results for dry matter yield are little affected by different input data in the north and west of the UK, but display marked variation in the south-east. Table 1 suggests that soil data are key to this variation; however, investigation of both model sensitivity and the distribution of differences in input and output data suggest that yield variations require further explanation.

Yield results follow a very distinct pattern of variation (see Fig. 2a, where there is a clear east-west divide) which is not evident with any of the variations in input data. The variation in yield more closely matches rainfall distribution (see Fig. 4b, showing an average for July) than any variations in inputs. In particular, it seems that while soil data variations are the main cause of yield variations, very few similarities are apparent in the distribution (see Fig 5a). Modelled yields are notably higher with the IGBP dataset in the south-east of the UK, and although the IGBP dataset tends to favour greater yields than HWSD, the distribution and magnitude of differences is spread fairly randomly across the UK.

From Figs. 1 and 2 it is clear that greater variation in yields coincides with areas of drought kill when using the HWSD dataset; although differences in the soil data are no larger in these areas than elsewhere, the combination with meteorological conditions means the model is closer to a kill threshold, at which point any differences in the input data are liable to be magnified by a step change in crop behaviour. It is thus the combination of inputs which causes large changes that would be unpredictable when considered individually.

As mentioned in Section 2.3, the field capacity and wilt point values used to represent HWSD were derived from the bulk density and texture of the soil layers using the Campbell method (Campbell, 1985). It is therefore difficult to fairly compare the soil datasets, especially given the difference in grid size, as noted in Section 2.2. However, the HWSD dataset does include values for the difference between field capacity and wilt point (rather than separate values), which when compared directly against IGBP values (rather than using the separate values derived from the Campbell method) still show large differences. Irrespective of the actual differences between the datasets, this study highlights the crucial role of soil water parameters and the combined effects of different inputs, as well as the need for careful use of soil data in environmental models.

### 4.2 Environmental and modelling implications

The results from different combinations of datasets raise important points about predicting crop growth and the potential consequences of environmental changes. While the effect of climate change on crop growth is subject to considerable attention, it is clear from this study that soil water parameters are also fundamental to potential yields. If climates become drier in summer, as predicted in areas including Europe, soil water storage will become increasingly critical. Greater attention should therefore be paid to preserving soil texture by the use of soil amendments and avoiding soil compaction, further to the existing focus on soil carbon sequestration and atmospheric $CO_2$ mitigation. From a modelling perspective, predictions of possible changes to soil conditions should ideally be considered alongside potential climatic changes.

While the effects of drought have been central to this study, it is likely that in some regions the effects of frost could play a similar role. Such areas would be of less interest for growing *Miscanthus*, since yields would be unlikely to be high in colder areas, but it is worth noting in a broader context, as well as the important role of step changes to model sensitivity in general.

Although the findings of this study depend primarily on differences between inputs rather than absolute values, the role of parameterisation should be considered ('parameterisation' is used here to refer to setting constants in the model to match field results). If different datasets were used to parameterise the model, results would clearly be altered; for example, if HWSD rather than IGBP soil data were used, the large areas of drought kill in the south east would likely no longer be apparent, since this would provide a poor fit with field data. This raises two important points about parameterisation. Firstly, it is necessary to recognise that parameterised model terms are likely to be dataset-specific, and that alternative datasets may not reliably provide model results for the conditions ostensibly described; rather, the conditions should be considered relative to those of the original dataset used for parameterisation. Secondly, by comparing results obtained from different input datasets, it is possible to assess the level of dependence on parameterisation for different aspects of the model, and potentially develop alternative model terms to respond to different inputs more accurately.

As a consequence of the dataset-specific nature of results, when using climate predictions it must be considered the extent to which changes in model results are due to changes in the predicted climate rather than simply the use of a different dataset. In order to minimise the problem, conditions should be considered relative to the base data rather than in absolute terms (assuming the base data are properly represented by the model), as described above, and results should be presented in relation to those obtained from the base values for the dataset, and not just in isolation.

## 5. Conclusions

The dependence of many environmental models on input datasets makes it particularly important to understand their effects on results. By comparing modelled yields obtained from a crop growth model using different meteorological and soil data, it is found that the combination of inputs affects results in ways which are unpredictable from individual parameters alone. While the model is generally relatively insensitive to changes in input datasets, it is possible in some areas to obtain significantly different yields using input data for ostensibly the same meteorological and soil conditions, particularly in areas with low levels of available soil water.

Differences between meteorological datasets are found to be fairly small across most of the region considered, with inter-annual variation often larger than differences between average datasets. Differences between soil datasets are very large in many areas, and although this is partly explained by having to derive equivalent values from one dataset, it underlines the difficulty of obtaining reliable soil data, and the significant role of pedotransfer functions when processing soil data. Variation in yields tends to be far smaller than soil data variation, except in locations where the combined effects of meteorological data make the crop vulnerable to a kill event.

The investigation highlights the importance of soil water parameters to modelling crop growth, and suggests that greater attention should be paid to soil water properties and preserving soil texture to avoid adverse effects on crops by increasingly dry conditions resulting from climate change. Differences between input datasets demonstrate the importance of considering the dataset-dependence of parameterised model terms, both for model validation and predictions based on alternative datasets.

## Acknowledgements

This work was partly funded by Shell Research Ltd. PS is a Royal Society-Wolfson Research Merit

Award holder. This work contributes to the Shell-funded "MiscanFor Development Project", the UK Energy Research Centre (UKERC)/NERC-funded project "Spatial Mapping and Evaluation of Energy Crop Distribution in Great Britain to 2050" (NE/H013415/1), the Energy Technologies Institute project "Ecosystem Land-Use Modelling and Soil Carbon GHG Flux Field Trial (ELUM)", and the EU-funded project "GHG-Europe". The authors are grateful to Mark Richards (University of Aberdeen, UK) for his assistance with plotting maps. The authors also wish to thank anonymous reviewers for their constructive suggestions.

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